MULTIGRADIENT FIELD ACTIVE CONTOUR FOR MULTILAYER DETECTION OF ULTRASOUND RECTAL WALL IMAGE

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Abstract-**This paper presents a novel multigradient field active contour algorithm with an extended ability for multiple object delineation, which overcomes some limitations of ordinary active contour models. One of the aims is to apply this technique for multilayer boundary detection of ultrasound rectal wall image, which is important in colorectal clinical diagnosis for rectal tumor staging. The core part in this algorithm is the proposal of multigradient vector field concept, which is used as a image forces for alternate constraints on deformation of the active contour. Its application on the ultrasound rectal wall image is also given to illustrate the multiple layer detection ability.**
***Keyword* - Active contour, snakes, deformable model, multigradient field algorithm**

I. INTRODUCTION

Colon and rectal cancers have emerged as common diseases in the developed country [1]. Like other cancers, the early stage diagnosis of the colorectal cancer is more important for getting good treatment. Currently, one of the most common techniques for screening test and early staging of the rectal tumors is endoscopic ultrasonography (EUS) [2], which can obtain a cross-sectional image of the rectal wall. In order to extract the positional information of the rectal tumor, surgeons need to view the ultrasound images slice by slice, then work out a 3D mental structure of rectum, and finally make a clinical diagnosis. So, the whole procedure is a time-consuming and tedious work for surgeons. On the other hand, to our knowledge, there are still no image processing methods that have been described in the literature to help surgeons complete this task.

The goal of our project is to develop an automatic analysis system to aid surgeons to cope with large quantities of rectal ultrasound images, involved rectal layer detection, rectal wall tumor detection, 3D reconstruction of rectal anatomic structure and corresponding quantitative analysis. However, the shape and layer structure detection based on 2D rectal wall images is an initial and important step to get the necessary information for 3D reconstruction. In this paper, we will focus on the algorithm for multilayer detection of rectal wall structure.

The layer's boundary detection of rectal wall is difficult because of the low spatial resolution of ultrasound images, the thin layer structure and the absence of the layer segment penetrated by the tumor. Therefore, conventional approaches, such as low-level edge detection and edge linking methods etc., are hare to complete our task. Other high-level methods do not meet the requirement for multilayer detection of the rectal structure [3, 4]. In the recent years, elastic deformable model (snakes) is one appreciated algorithm used by many researchers for boundary detection in image processing [5, 6, 7, 8]. The name "deformable models" is originated from the elastic theory in physics. The whole object matching is a searching procedure that uses the optimal approximation theory to obtain the energy minimum [9]. In this project, with snakes method, the anatomical knowledge of the rectum can be integrated into layer detecting procedures. Due to the characteristic of closed active contour, snakes method can obtain a full closed boundary despite the existence of the broken layers. Furthermore, the snakes method can fulfil the boundary detection and object recognition at same time, which cannot be done by low level method. But, some inherent shortcomings in "snakes" algorithm limit its application in this project. In order to automatically outline each muscular layer's boundary of the rectal wall, the approach followed in this paper will introduce a novel multigradient field active contour model developed by authors, based on the framework of elastic deformable model.

II. MULTIGRADIENT FIELD ACTIVE CONTOUR MODEL

In order to display the full anatomical structure, the muscular layer detection need to complete the a few tasks, such as border detection and object recognition etc. A basic idea is as follows. Firstly, set up an initial active contour in the balloon area of the rectal image. Then, expand this initial model to obtain the inside boundary of the innermost layer. Subsequently, use this boundary as the new contour and continuously expand to extract the next layer's boundary. This method is repeated to detect each muscular layer from inside to outside.

A. *Multigradient Field Active Contour Model*

We have set up a novel active contour model based on the framework of the traditional deformable model, as follows:

$$E_{snake} = \int E_{\text{int}}(v(s)) + w_{image}E_{image}(v(s)) + w_{adpt}E_{\exp}(v(s))ds \tag{1}$$

where, $v(s) = [x(s), y(s)]$ represents the deformable model. Internal energy is the same as that in the traditional snakes, $E_{\text{int}}(v(s)) = \int ((\alpha(s)\left|v_s(s)\right|^2 + \beta(s)\left|v_{ss}(s)\right|^2)/2$ which is used to compose the regularity of the curve (α and β are

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parameters to constrain the snakes' tension and rigidity, and $v_s(s)$ and $v_{ss}(s)$ are first- and second-derivatives with respect to arc length s). Image energy E_{image} is an external energy that comes from the image features so that it takes on its smaller values at the features of interest. Here, a novel multigradient field algorithm is proposed to compute the multigradient vectors as features. Adaptive expanding energy $E_{\exp}$ is an external energy. The corresponding force derived from it can make the active contour model expanded with adaptive adjustable feature, especially in the homogeneous region that has no gradient field. w is weighting parameter.

Using the calculus of variations and solving the Euler equations give the minimization of above equation [9]. In the following, only two important formulae are given for further discussion and comparison. The Euler equations obtained from the Eq. (1) can be described as following two independent parts according to x and y coordinates:

$$\frac{\partial}{\partial s}\left(\alpha(s)\left|\frac{\partial x(s,t)}{\partial s}\right|\right)+\frac{\partial}{\partial s^2}\left(\beta(s)\left|\frac{\partial^2 x(s,t)}{\partial s^2}\right|\right) + w_{image}\frac{\partial E_{image}(x,y)}{\partial x} + w_{adpt}\frac{\partial E_{\exp}(x,y)}{\partial x} = 0 \quad (2a)$$

$$\frac{\partial}{\partial s}\left(\alpha(s)\left|\frac{\partial y(s,t)}{\partial s}\right|\right)+\frac{\partial}{\partial s^2}\left(\beta(s)\left|\frac{\partial^2 y(s,t)}{\partial s^2}\right|\right) + w_{image}\frac{\partial E_{image}(x,y)}{\partial y} + w_{adpt}\frac{\partial E_{\exp}(x,y)}{\partial y} = 0 \quad (2b)$$

We can use finite differences to derive approximations to the differential and double differential of the above function. Substituting these in the above equations will give a pair of systems of equations for finding x and y coordinates that minimizes the energy function of the active contour. Each point in the active contour can be converted to vector notation with $\mathrm{v}_i = (x_i, y_i)$. The final numerical solution is,

$$\mathrm{x}_t = (\mathrm{C} + l\mathrm{I})^{-1}(l\mathrm{x}_{t-1} - w_{image}\mathrm{f}_{\mathrm{img\_x}}(\mathrm{x}_{t-1}, \mathrm{y}_{t-1}) - w_{adpt}\mathrm{f}_{\mathrm{adpt\_x}}(\mathrm{x}_{t-1}, \mathrm{y}_{t-1})) \quad (3a)$$

$$\mathrm{y}_t = (\mathrm{C} + l\mathrm{I})^{-1}(l\mathrm{y}_{t-1} - w_{image}\mathrm{f}_{\mathrm{img\_y}}(\mathrm{x}_{t-1}, \mathrm{y}_{t-1}) - w_{adpt}\mathrm{f}_{\mathrm{adpt\_y}}(\mathrm{x}_{t-1}, \mathrm{y}_{t-1})) \quad (3b)$$

Where, $f_{img\_x}(i) = \partial E_{image}(x,y)/\partial x_i$,
and $f_{img\_y}(i) = \partial E_{image}(x,y)/\partial y_i$ are image forces;
and $f_{adpt\_x}(i) = \partial E_{adpt}(x,y)/\partial x_i$ and
$f_{adpt\_y}(i) = \partial E_{adpt}(x,y)/\partial y_i$ are adaptive external forces. C is a pentadiagonal matrix including some parameter information such as α and β, and l is a step size. t denotes time step, while x_t and y_t are vectors including the x and y co-ordinates of the active contour on time t.

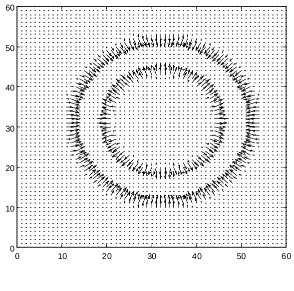
B. *Multigradient Vector Field Model*

The idea through the approach is to detect the rectal layer one by one from inner to outer by deformable model. Therefore, when one layer is delineated, the algorithm should be able to deform the active contour again and search the next layer automatically. But during the experiment, it is found that after detecting the inner boundary the active contour model would not expand as expected. This is precisely happened in traditional snakes algorithms – once an active model arrives at the energy minimum, it will not deform again.

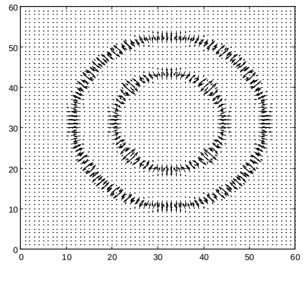
By analyzing traditional snakes formulae, we can find that image energy is a gradient vector after performing a gradient operation on the original image. However, the image force, which drives the deformation of the active contour, is a gradient vector obtained from the gradient operation of the image energy component. It means that image force is a second-order derivative derived from image.

In order to explain the multigradient field algorithm, following two kinds of gradient vector fields are defined to clarify the purpose (A ring-shaped image (a black ring on a white background) is used as an example). (1) *First-order gradient vector field (FOGVF)* – Gradient vector field obtained from the gradient operation on the original image. The corresponding image is called first-order gradient image (map); (2) *Second-order gradient vector field (SOGVF)* – Gradient vector field obtained from the gradient operation on the first-order gradient image. The corresponding image is called second-order gradient image (map).

Fig. 1 shows these two different gradient vector fields operating on above ring-shaped image. From Fig. 1 (b), it is found that the edge of the ring is constrained by two opposite forces – centripetal force and centrifugal force. These two forces act as image forces that have the active contour attracted by edge and kept in the status of energy minimum. On the other hand, the centripetal force is just the force that prevents the active contour from expanding and searching outer border according to our original thought. However, from the first-order gradient vector field, we can find that the centripetal gradient vector in the inner border disappears because of the gradient feature of the original image. This feature is exactly what we want, by which the active contour escapes from the gravity of the inner border.



(a) Gradient vector field based on original image – first-order gradient vector field



(b) Gradient vector field based on gradient image–second-order gradient vector field

Fig. 1. First-order gradient vector field and second-order gradient vector field of the ring-shaped image.

Based on above analysis, a novel active contour algorithm incorporating multigradient vector field (multi-GVF) algorithm is developed. This model named multigradient field active contour model can complete the multilayer border detection of the rectal wall structure. Fig. 2 shows how to detect the inner border and outer border of a ring by this algorithm. A detailed procedure about the algorithm is described as follows:

1. Compute the FOGVF and SOGVF of the image.
2. Under the constraint of the SOGVF, deform the active contour model and obtain the inner border (Fig. 2 (a)). The corresponding numerical equations are,

$$\begin{aligned} \mathrm{x}_t = (\mathrm{C}+l\mathrm{I})^{-1}(l\mathrm{x}_{t-1} - w_{image}\partial \mathrm{E}_{\mathrm{image}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})/\partial \mathrm{x}_{t-1} \\ - w_{adpt}\mathrm{f}_{\mathrm{adpt\_x}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})) \end{aligned} \tag{4a}$$

$$\begin{aligned} \mathrm{y}_t = (\mathrm{C}+l\mathrm{I})^{-1}(l\mathrm{y}_{t-1} - w_{image}\partial \mathrm{E}_{\mathrm{image}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})/\partial \mathrm{y}_{t-1} \\ - w_{adpt}\mathrm{f}_{\mathrm{adpt\_y}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})) \end{aligned} \tag{4b}$$

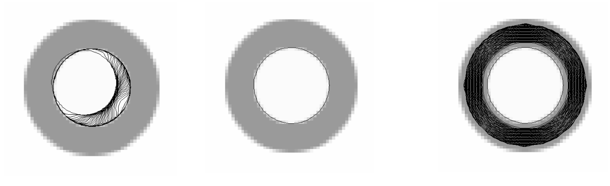
3. Use the above result as the new initial contour, deform the active contour model again under the constraint of the FOGVF. The corresponding numerical equations become

$$\begin{aligned} \mathrm{x}_t = (\mathrm{C}+l\mathrm{I})^{-1}(l\mathrm{x}_{t-1} - w_{image}\mathrm{E}_{\mathrm{image}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1}) \\ - w_{adpt}\mathrm{f}_{\mathrm{adpt\_x}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})) \end{aligned} \tag{5a}$$

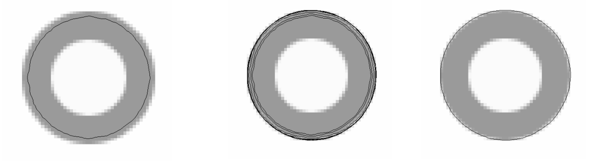
$$\begin{aligned} \mathrm{y}_t = (\mathrm{C}+l\mathrm{I})^{-1}(l\mathrm{y}_{t-1} - w_{image}\mathrm{E}_{\mathrm{image}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1}) \\ - w_{adpt}\mathrm{f}_{\mathrm{adpt\_y}}(\mathrm{x}_{t-1},\mathrm{y}_{t-1})) \end{aligned} \tag{5b}$$

As the gradient vector field is first-order GVF, the energy minimum position that deformable model reached is not the real edge of the ring, as shown in Fig. 2 (c).

4. This step is a fine-tuning or refinement of the final border position. The SOGVF is used again like step 2, and the contour model continues to deform mainly under the second-order gradient vector, the internal force and the adaptive expanding force. Finally, when energy minimum is reached, the accurate location of the outer border is obtained (Fig. 2 (d)).



(a) Extract inner boundary under SOGVF (b) Escape from the attraction of Inner border under FOGVF



(c) The intermediate result (d) Extract the outer boundary under SOGVF again.

Fig. 2. Inner layer and outer layer detection by two different GVFs

If there are more circular layers, steps 3 and 4 can be repeated to complete the detection of each layer.

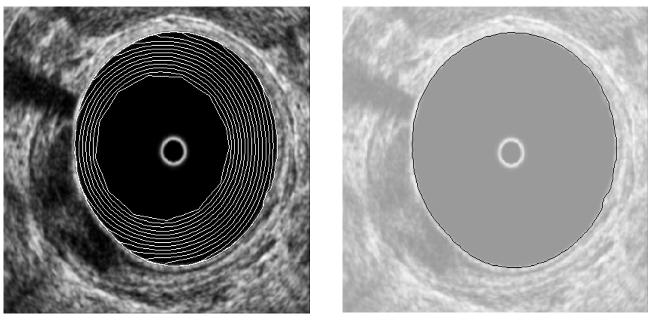
III. EXPERIMENTAL RESULTS

The pictures given in Fig. 3 demonstrate the deformation process and the results of multigradient field active contour for boundary detection for different layers of rectal wall. According to the multigradient field algorithm, actually, three different gradient vector fields and their corresponding gradient maps are computed and used as image forces in different detecting phase. They are:

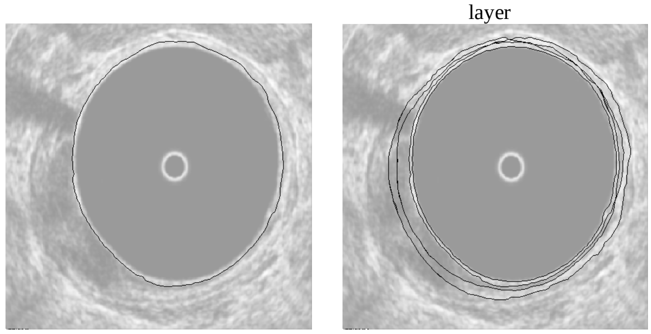
- First-order gradient vector field and first-order gradient map of original image;
- Second-order gradient vector field and second-order gradient map of original image;
- First-order gradient vector field and first-order gradient map of the inverted image whose grays are assigned their mirror transparency.

Fig. 3 (a) shows the detection for the inner boundary of rectal wall, while Fig. 3 (b) shows inner boundary of the first layer of rectal wall. From the result, we can find that multigradient field algorithm can give a good detection of the edge because of relatively good edge features. The adaptive force derived from $w_{adpt}E_{\exp}$ actually supplies a more flexible and stable control for the deformation of the active contour than traditional algorithm.

Deformation starting from the location shown in Fig. 3 (b) and under the control of two different gradient fields–



(a) Searching under SOGVF (b) Inner boundary of the first layer



(c) Outer boundary of the first layer (d) Inner 3 layer's boundaries

Fig. 3. Experiment: detect the probe boundary and three layers' boundary of the rectal wall (Note: Except (a) is an original grey-level image, the other images are diluted as background of each picture for convenient view of the delineated boundary).

FOGVF and SOGVF, the deformable model can successfully extract the outer boundary shown in Fig. 3 (c). In the whole procedure, FOGVF from original image, which can help active contour escape from the capture range of the inner boundary, controls the first stage deformation and obtains a temporary result, which lies between the inner edge and the outer edge of the first layer.

In the second stage, active contour deforms under SOGVF and finally detects the outer boundary. Fig. 3 (d) shows the boundaries of the inner three layers obtained by multigradient field algorithm. Though the second layer is very thin, it is found that the new algorithm can accurately distinguish and extract the second layer. Of course, in some segment, because of rather thin layer and the original image's quality, there are some overlapping parts. The parameter selection for the model is given in Table 1.

TABLE I

Parameters setting for mltigradient field active contour

Gradient Vector Field	α	β	w_{image}	w_{adpt}	l
SOGVF	0.024	0	20	0.007	1
FOGVF	0.030	0	2	0.030	1

Three surgeons were invited to evaluate the results of the algorithm. Eight image slices were used for test. By comparing the detected boundaries with their manual tracing, the surgeons considered that the detected boundaries were suitable for clinical application. A further quantitative assessment like accuracy and stability of the algorithm is in progress.

IV. Conclusions and discussion

The investigation of rectal wall multilayer delineation on ultrasound images was motivated by the need to detect and stage the tumor of the rectum for clinical application. The first-order gradient and second-order gradient vector fields are given and based on them, a novel multigradient vector field algorithm is proposed and introduced into the active contour model. This algorithm enables the active contour to escape from the trammel of the present layer and continue the next layer searching and finally accomplish the multilayer detection. Adaptive force, which is able to make a compensation between internal force and image force, especially in homogeneous regions in an image, also plays an important role in the practical application.

Several problems should be considered in the future. Although the detection results generally display the real positions of the boundary of normal layers, the detected boundaries located on artifacts and tumor area, due to the effect of internal force, deviate from their real position.

Another problem is that during the process of deformation the active contour sometimes is easily attracted by some "isolated islands" and forms an irregular border. The reason is due to the irregularity of the boundary and some small broken segments on the layer. Pre-processing the image may be able to solve these defects inherent with ultrasound images. In this paper, we try to emphasize the general features of the algorithm, so only a little prior knowledge about rectal anatomical structure was incorporated into the algorithm. More prior knowledge and constraints may be incorporated into the basic model soon. To assess the performance of the automatic boundary detection algorithm, a set of quantitative assessment rules should be set up and the further experiments should be done.

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